Variational data assimilation of lightning with WRFDA system using nonlinear observation operators

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Outline

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Present lightning data assimilation effort

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Introduction

- Assimilating Earth Networks Total Lightning Network (ENTLN) data during two cases of severe weather: a supercell and a squall line.
- Weather Research and Forecast (WRF) model and variational data assimilation techniques at 9 km spatial resolution - 3D-VAR, 1D+nDVAR (n=3,4); a highly non-linear observation operator based on convective available potential energy (CAPE) as proxy.
- Data from the ENTLN at 9km resolution serve as a substitute for those from the upcoming launch of the GOES Lightning Mapper (GLM)

Previous lightning data assimilation efforts

- Alexander et al. (1999) used data derived from spaceborne and lightning-derived rainfall measurements to improve simulated latent heating rates.
- Newtonian Nudging - Fita et al 2009, Pessi and Businger 2005, 2009 - empirical relationship between lightning and convective rainfall, Papadopulos et al. 2009; MM5, ECMWF; Mansell et al 2007 - flash data used as a proxy for the presence or absence of deep convection; Fierro et al. 2012 - the lightning data and simulated graupel mixing ratio locally increases the water vapor mixing ratio (relative humidity).
- EnKF (Hakim et al. 2008) - Lightning data used as a proxy for convective rainfall. Hybrid Variational ensemble data assimilation using WRF - NMM model (Zupanski, 2010).
- Fierro et al. 2013 - an explicit lightning physical package within WRF using a bulk lightning model (BLM) based on charging of hydrometeors, polarization of cloud water and exchange of charge during collisional mass transfer.

Present lightning data assimilation effort

- The lightning operator assumes the form Barthe et al. (2010), Price and Rind 1992, Kirkpatrick et al. (2009)

$$H(X) = 5 \cdot 10^{-7} \cdot (0.677 \cdot \sqrt{2 \cdot CAPE} - 17.286)^{4.55}$$

- The input X: 1D vertical arrays of pressure, temperature, water vapor mixing ratio, and geopotential height.

- Approach: the variational DA schemes adjust the vertical temperature profile at each grid point where innovation vectors are positive.

- Linear correlation coefficients between lightning observations and model simulated CAPE are 0.693 and 0.6719 for the two cases.

Incremental 4D-VAR data assimilation

- The incremental approach is designed to find the analysis increment $\delta x = X - X_0^b$ that minimizes

$$J(\delta x) = \frac{1}{2}\delta x^T \mathbf{B}^{-1}\delta x + \frac{1}{2}\sum_{k=1}^{N}(d_k - \mathbf{H}_k\mathbf{M}_k\delta x)^T \mathbf{R}_k^{-1}(d_k - \mathbf{H}_k\mathbf{M}_k\delta x)$$

- $\mathbf{R}_k$ is the observation error covariance matrix, $\mathbf{B}$ contains the background error covariance matrix, $d_k = Y_0^k - H_k M_k X_0^b$ are the innovation vectors.

- $M_k(X_0) = M_{0\to k}(X_0)$; $\mathbf{M}_k$ and $\mathbf{H}_k$ denote the tangent linear versions of the forecast model and observation operator.

Methodology for lightning assimilation

- 3D-VAR direct assimilation of lightning is restricted by tangent linear assumption.
- **Requirement**: at least a small amount of CAPE in the model background (otherwise the lightning sensitivities are close to zero) and background CAPE $\geq 325.973 Jkg^{-1}$.
- **B** - ensemble statistics; vertical and horizontal error covariances - EOF functions and a recursive filter; forecasts generated over 1 month length.
- The lightning observations - uncorrelated. The observation error covariance matrix is diagonal.
- For simplicity our assimilation tests were performed using an identity matrix for the observation error covariance matrices $\mathbf{R}_k$.

1D+nDVAR(n=3,4)

- (1D-VAR): the raw lightning data - increments of temperature that are added to the model background to generate column temperature retrievals;(nD-VAR): these temperature pseudo observations are assimilated as conventional observations into the variational WRFDA systems.
- **B** for temperature profiles - NMC method; 12 h and 24 h forecasts valid at the same time from a one month dataset generated by the WRF model.
- 1D-VAR analysis: Quasi-Newton limited memory conjugate gradient
- Advantages: additional quality control tests, better handle the less linear inversion problem, present 'smooth' pseudo observations to nD-VAR, filter the other nD-VAR control variables, use **B** twice.

NWP model

- Non-hydrostatic WRF model V3.3 with ARW core.
- Outer domain - 27 km resolution; a two way nested inner domain - 9 km horizontal grid spacing $\approx$ 1413 km $\times$ 1170 km. 60 vertical levels were selected to cover the troposphere. The grid size of the 9km model domain is $157 \times 130 \times 60$.
- For initial and boundary conditions the NCEP Global Forecasts System (GFS) 1 degree resolution final analyses were used.
- Kain-Fritsch cumulus parameterization, Yonsei planetary boundary layer scheme, rapid radiative transfer model (RRTM), Dudhia scheme and a single moment, 6 class, cloud microphysics scheme.

Results

- 6 h of model spin up between 1200 UTC and 1800 UTC; assimilation window varying between 2 to 6 h; an additional $3-7$ h forecast, ending at 0300 UTC of the next day.
- Two control variable settings: 1. unbalanced temperature (configuration I - C1); 2. unbalanced temperature, stream function, unbalanced velocity potential, unbalanced surface pressure, and pseudo relative humidity (configuration II - C2).
- 3D-VAR and 1D+3D-VAR schemes: a cycling procedure was adopted to assimilate the lightning observations between 1800 UTC and 0000 UTC.
- The first guesses were obtained by integrating the previous 3D-VAR analysis 1 h in time using the WRF model.
- 1D+4D-VAR scheme: we used a 2 h assimilation window between 1800-2000 UTC.

Results

- The number of lightning observations utilized by the 3D-VAR scheme was greater than those used by the 1D+nD-VAR schemes.
- 1D-VA RQC tests: a. The vertical background error covariance matrix conditioned the 1D-VAR minimization; b. $|H(x_a) - H(x_b)| < 0.2$;
- The average flash rates used to generate the successful 1D-VAR retrievals were 5.343 and 7.065 flashes $(9\mathrm{km})^{-2}$ min^{-1}, respectively, for the 27 April and 15 June storms.
- The retrievals were checked for vertical consistency (super adiabatic lapse rate) and were adjusted to dry adiabatic in unstable layers using OBSPROC (the WRFDA Running Observation Preprocessor).

Results

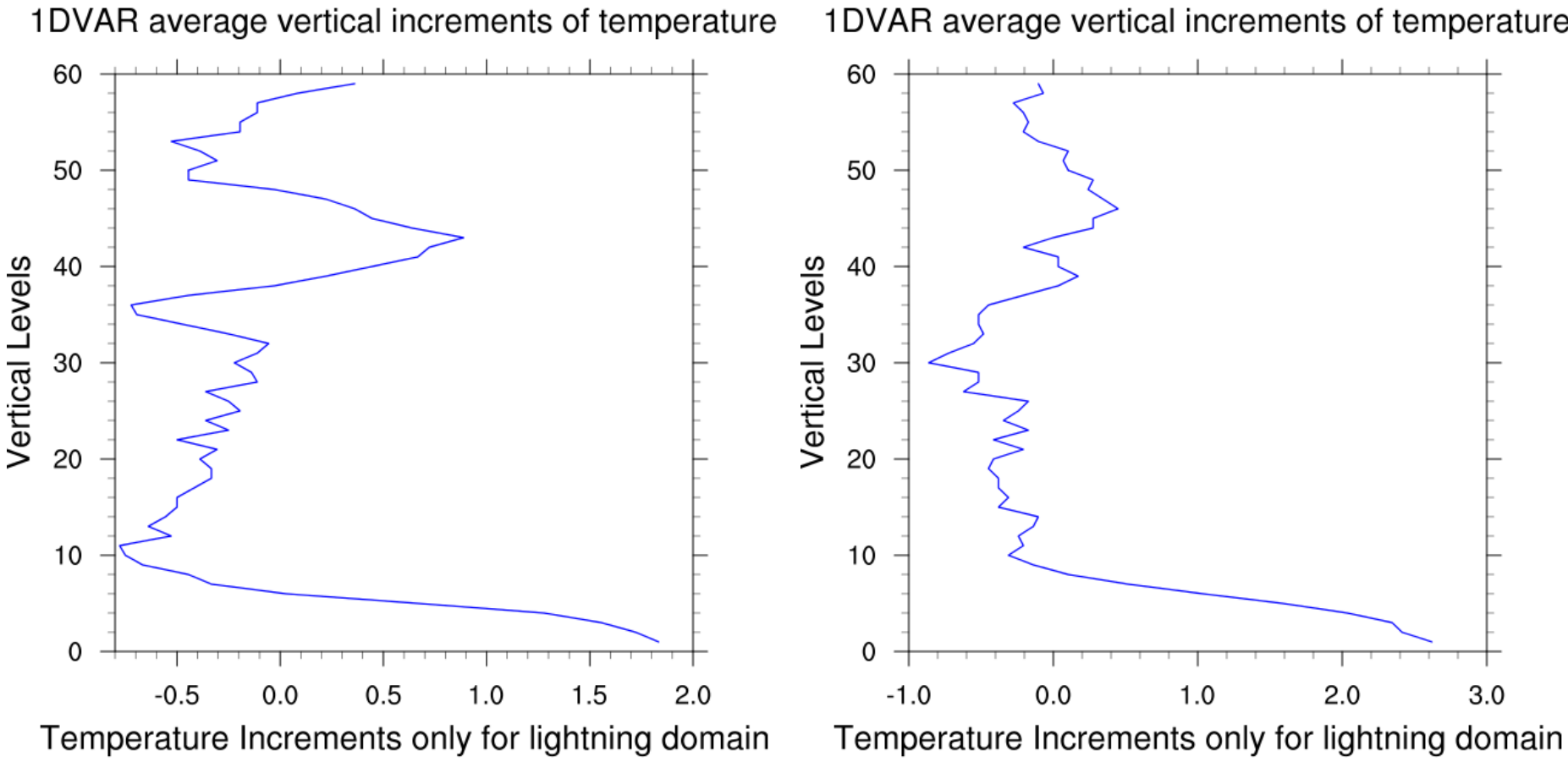
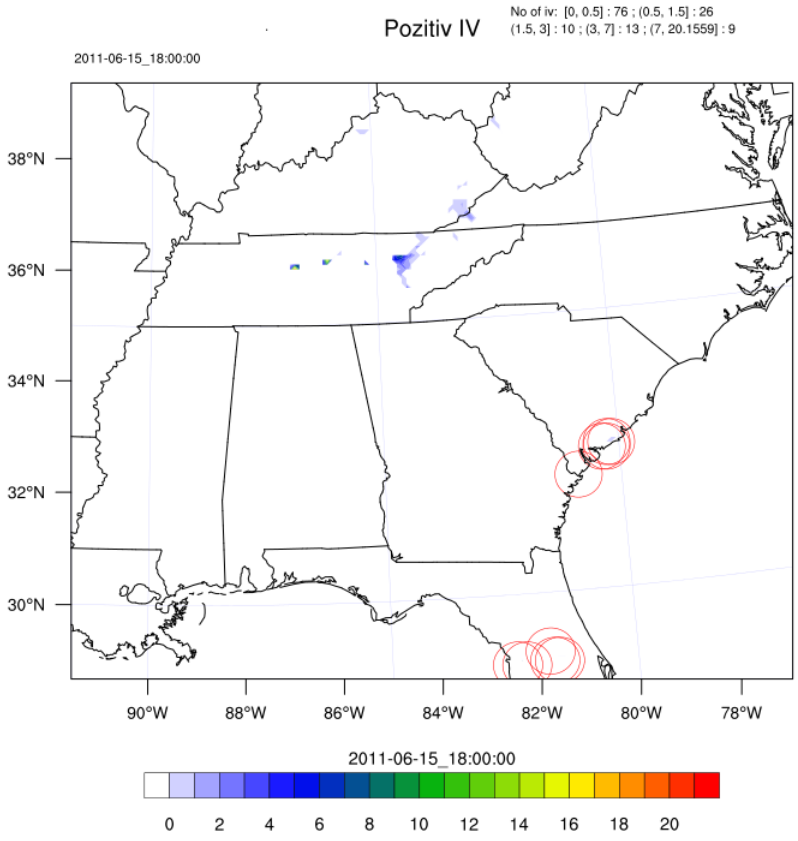


Figure: Average vertical increments of temperature (K) for the successful 1DVAR retrievals at 1800 UTC on 27 April (left) and 15 June (right).

Results



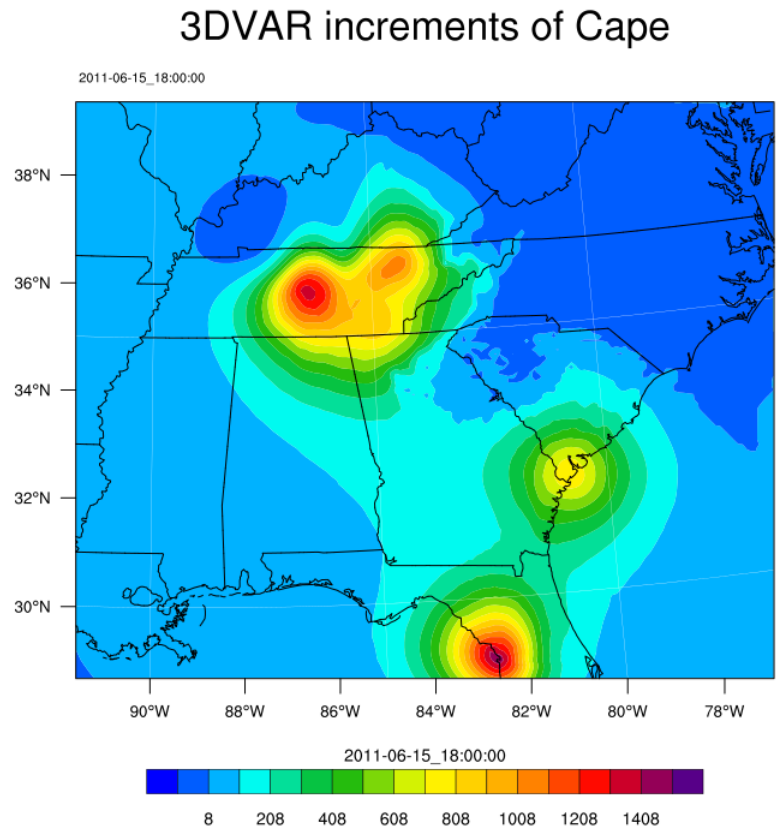


Figure: Innovation vectors (flashes $(9\mathrm{km})^{-2}\mathrm{min}^{-1}$) before (left) and corresponding increments of CAPE (right; Jkg^{-1}) following 3DVAR lightning assimilation at 1800 UTC 15 June.

Results

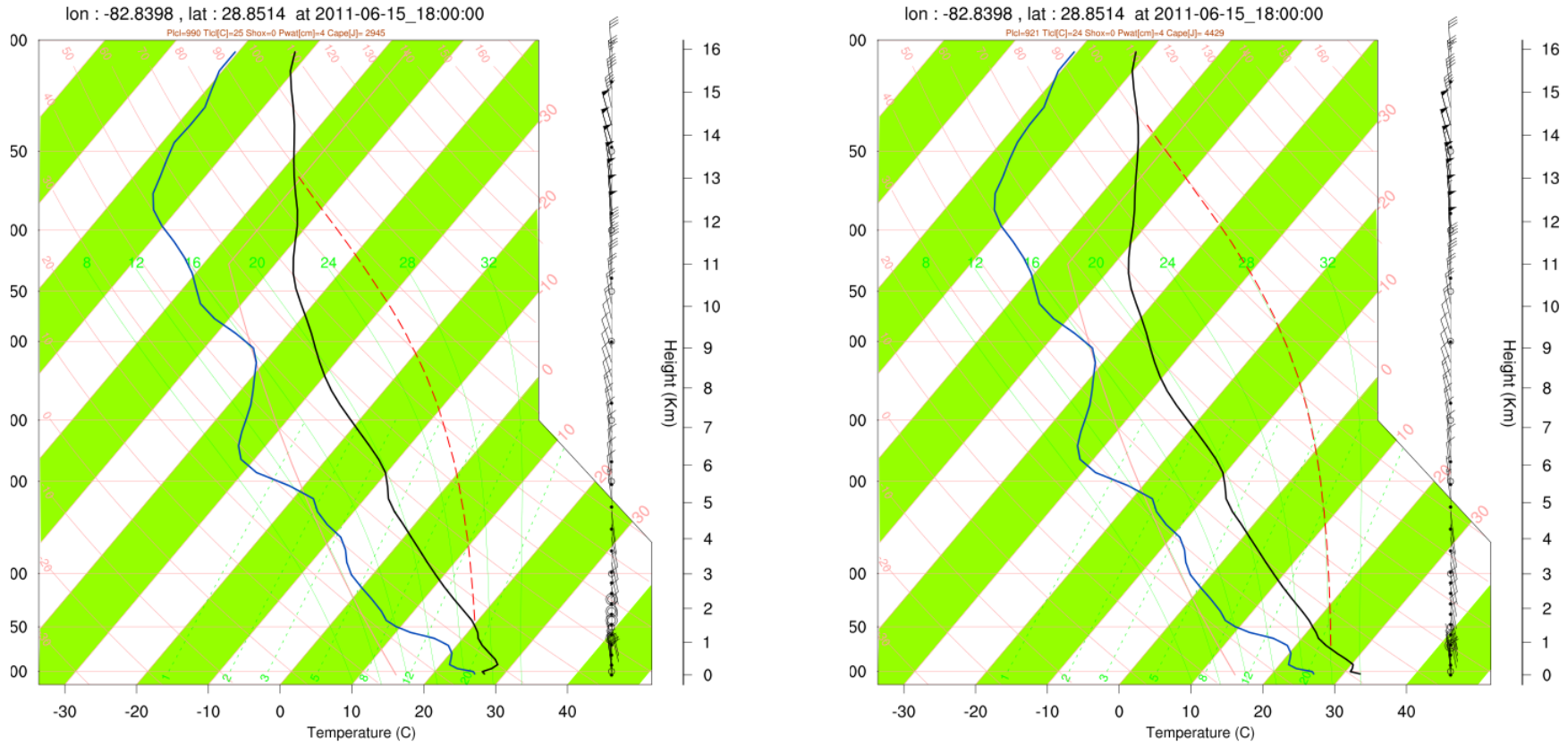


Figure: Skew-T diagrams (left, no lightning; right, after 3DVAR assimilation of lightning) at 1800 UTC 15 June at the location of greatest change in CAPE observed in central Florida with air temperature (C, black line), dew point temperature (C, blue line), and horizontal wind (*kt*, barbs along right axis).

Results

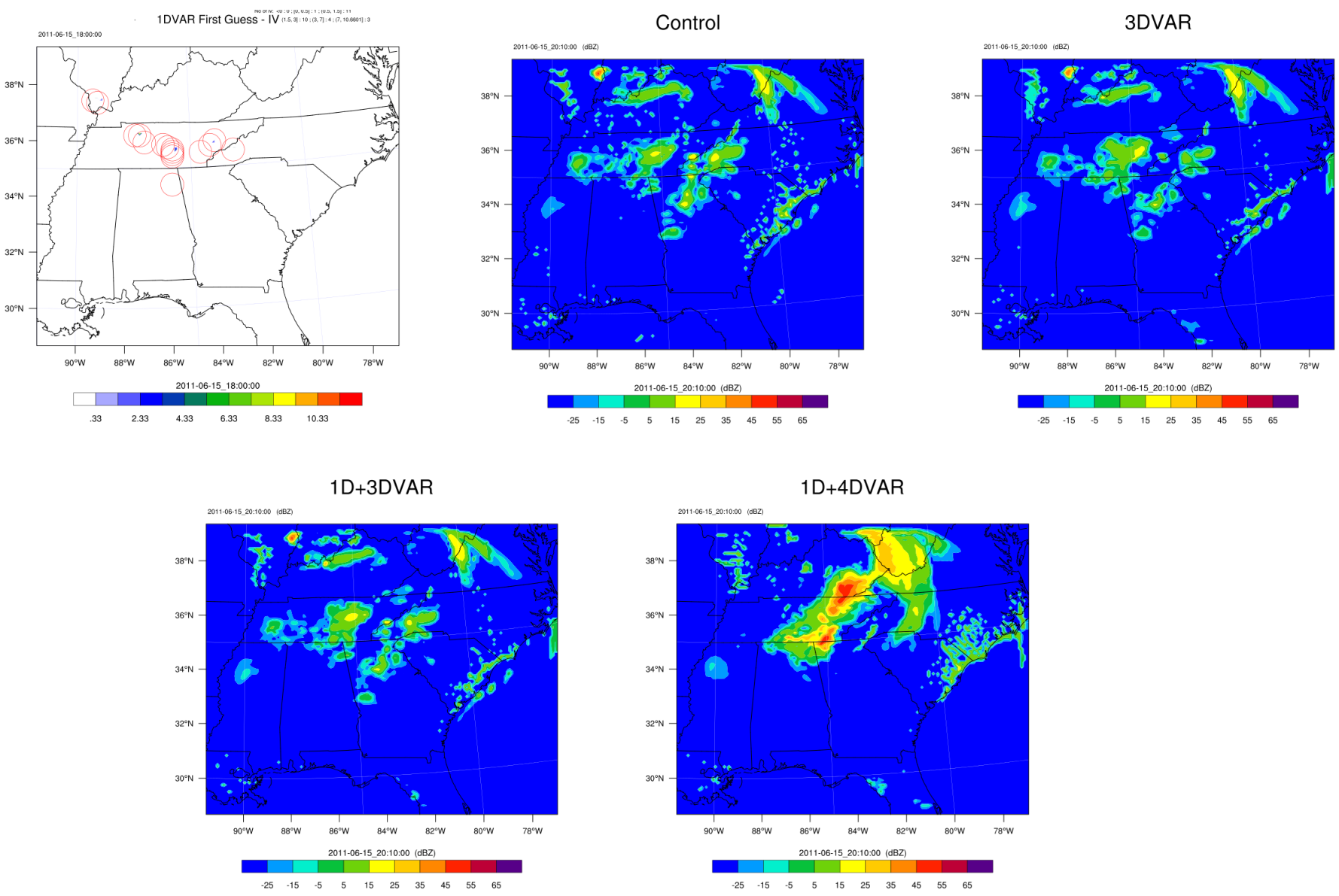
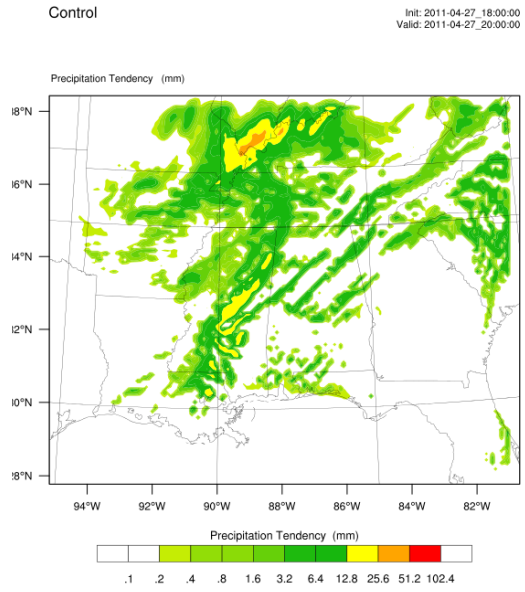


Figure: Simulated radar reflectivity (dBZ) at 2010 UTC 15 June

Results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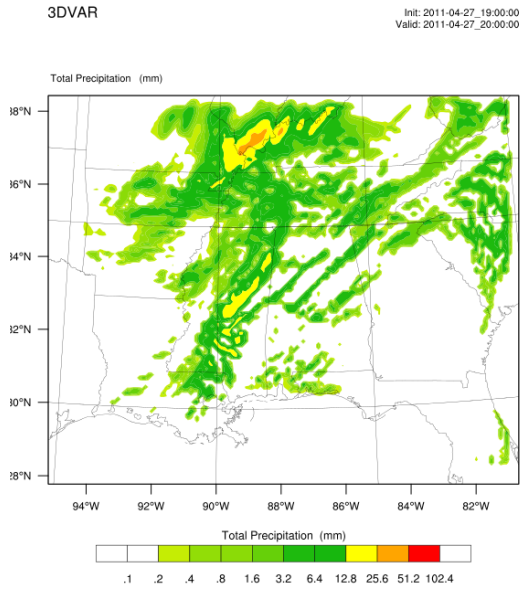
94°W 92°W 90°W 88°W 86°W 84°W 82°W
Precipitation Tendency (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4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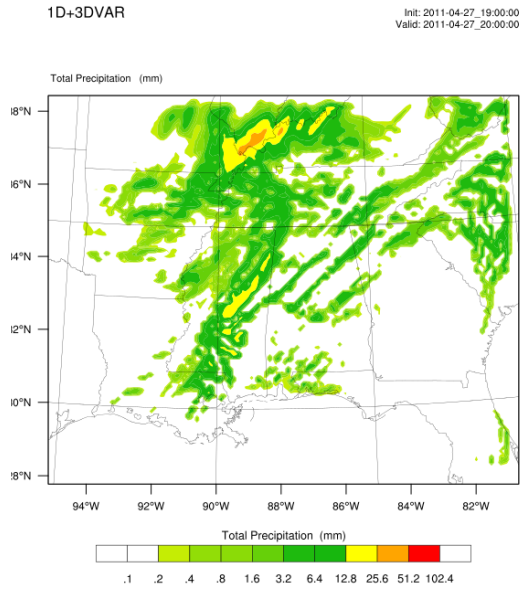
Total Precipitation (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4


1D+3DVAR
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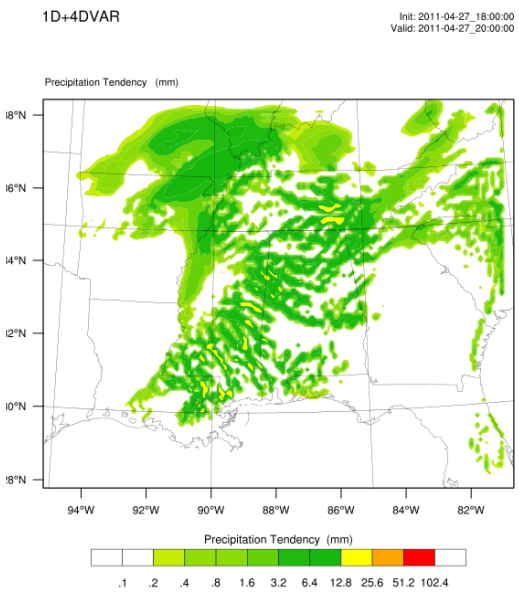
Total Precipitation (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4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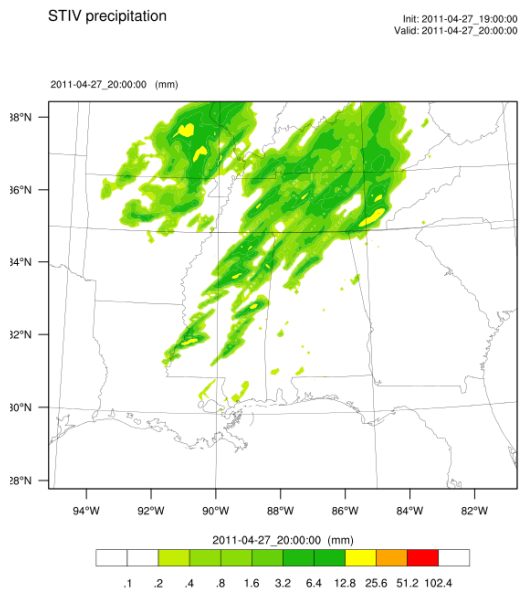
94°W 92°W 90°W 88°W 86°W 84°W 82°W
Precipitation Tendency (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4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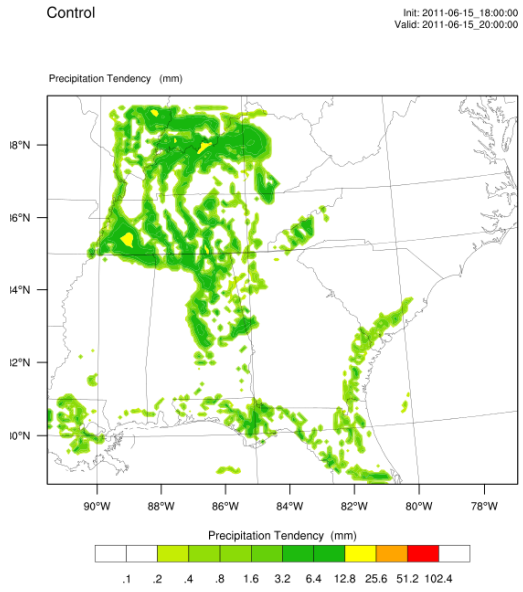
2011-04-27_20:00:00 (mm)
94°W 92°W 90°W 88°W 86°W 84°W 82°W
2011-04-27_20:00:00 (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4

Results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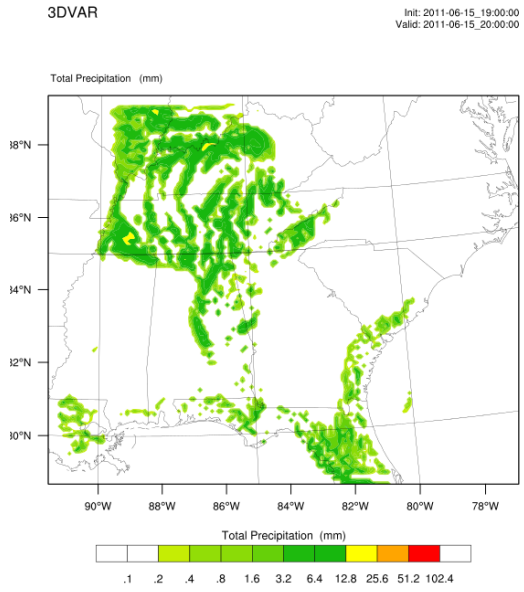
90°W 88°W 86°W 84°W 82°W 80°W 78°W
Precipitation Tendency (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4


3DVAR
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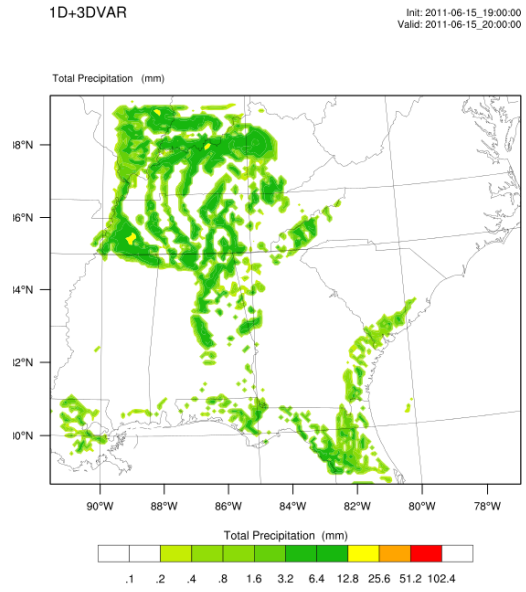
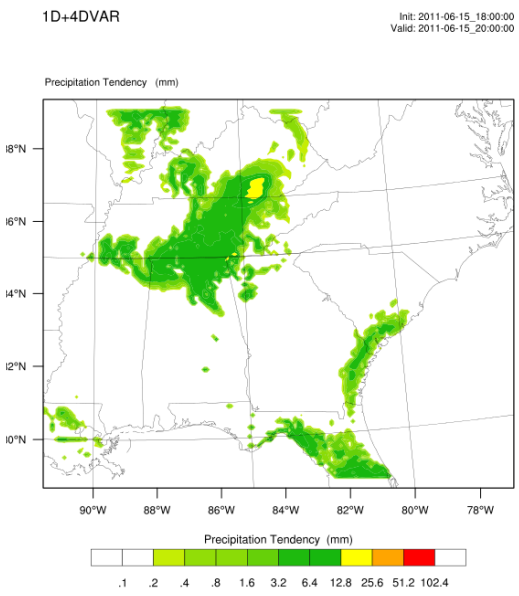
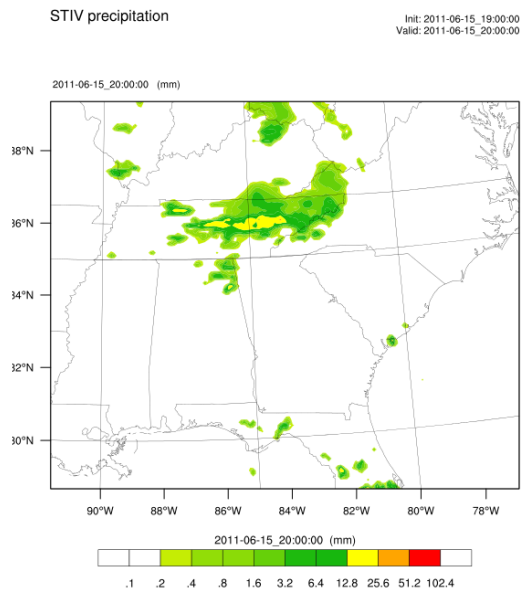
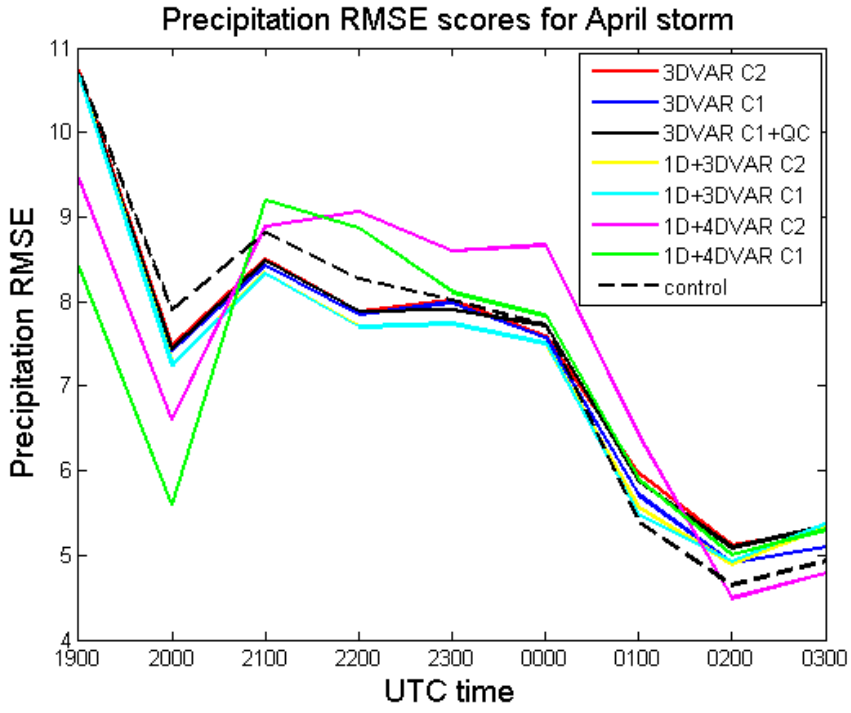
Total Precipitation (mm)
90°W 88°W 86°W 84°W 82°W 80°W 78°W
Total Precipitation (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4


1D+3DVAR
Init: 2011-06-15_19:00:00
Valid: 2011-06-15_20:00:00
Total Precipitation (mm)
90°W 88°W 86°W 84°W 82°W 80°W 78°W
Total Precipitation (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4


1D+4DVAR
Init: 2011-06-15_18:00:00
Valid: 2011-06-15_20:00:00
Precipitation Tendency (mm)
90°W 88°W 86°W 84°W 82°W 80°W 78°W
Precipitation Tendency (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4


STIV precipitation
Init: 2011-06-15_19:00:00
Valid: 2011-06-15_20:00:00
2011-06-15_20:00:00 (mm)
90°W 88°W 86°W 84°W 82°W 80°W 78°W
2011-06-15_20:00:00 (mm)
.1 .2 .4 .8 1.6 3.2 6.4 12.8 25.6 51.2 102.4

Results



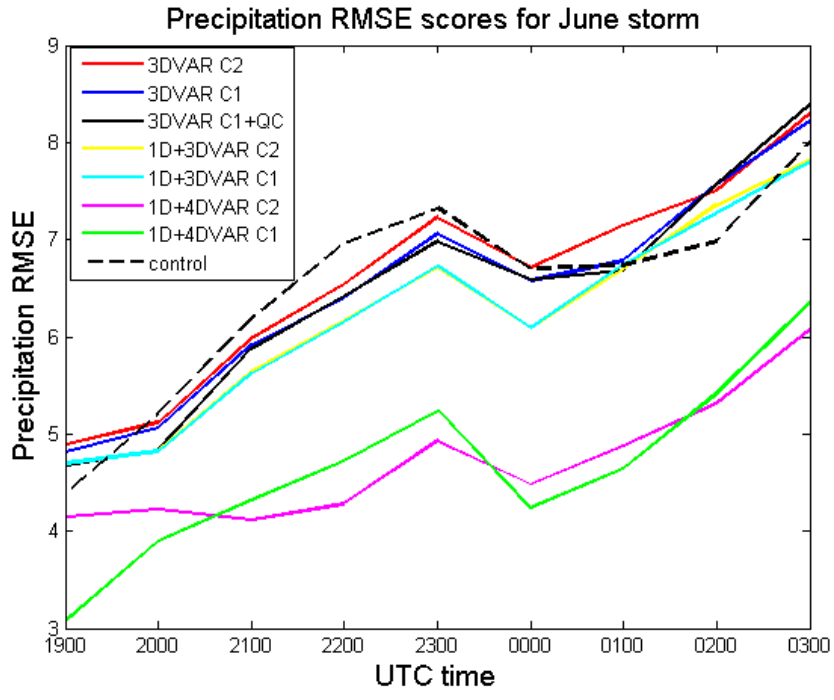


Figure: RMSE of precipitation (mm) for both study days compared with stage IV observations. Assimilation was not performed after 2000 UTC for the 1D+4D-VAR simulation, and not after 0000 UTC for the 3D-VAR and 1D+3D-VAR approaches.

Conclusions

- 3D-VAR and 1D+nD-VAR (n=3,4), have been developed to assimilate lightning data into WRF.
- The observed flash rates warm the atmosphere near the surface, increase the CAPE, and thereby strengthen the simulated convection at locations of lightning.
- Hourly precipitation patterns, its statistics, and radar reflectivity were improved by assimilating the lightning observations.
- The 1D+4D-VAR approach performed best, improving the precipitation areas and totals by 25% and 27.5% compared to the control run on the two days that were studied during the assimilation window.
- RMSE of the 1D+4D-VAR simulations were the smallest during a subsequent 7 h forecast period on 15 June. However, on 27 April the 1D+4D-VAR forecasts outside the assimilation window were not improved.

Conclusions

- Two control variable configurations. The precipitation RMS errors showed that the best configuration includes only temperature as control variable.
- The assimilated number of observations can be increased by including observations that have negative innovation vectors.
- The 1D-VAR algorithm failed to converge mostly because of the lack of CAPE in some regions of the first guess fields.
- A nudging scheme - artificially increase background CAPE to an amount that allows the observation operator to sustain the lightning data assimilation - decrease convergence failure rate of 1D-VAR min algorithm.
- Results of the 1D+4D-VAR lightning assimilation and short term forecasts indicate improvements in precipitation scores and show promise for operational implementation.